

**AFRL-IF-RS-TR-2005-311**  
**In-House Report**  
**August 2005**



# **COMPLEMENTARY ADVANCED FUSION EXPLORATION**

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**AIR FORCE RESEARCH LABORATORY  
INFORMATION DIRECTORATE  
ROME RESEARCH SITE  
ROME, NEW YORK**

## **STINFO FINAL REPORT**

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REPORT DOCUMENTATION PAGE			Form Approved OMB No. 074-0188	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing this collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503				
1. AGENCY USE ONLY (Leave blank)		2. REPORT DATE AUGUST 2005		3. REPORT TYPE AND DATES COVERED In-House Report Jan 02 – Jun 05
4. TITLE AND SUBTITLE COMPLEMENTARY ADVANCED FUSION EXPLORATION			5. FUNDING NUMBERS C - N/A PE - 62702F PR - 459E TA - CA WU - FE	
6. AUTHOR(S) Mark G. Alford, Eric C. Jones, Adnan Bubalo, Melissa Neumann, Michael J. Greer				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Air Force Research Laboratory/IFEA 525 Brooks Road Rome New York 13441-4505			8. PERFORMING ORGANIZATION REPORT NUMBER  N/A	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) Air Force Research Laboratory/IFEA 525 Brooks Road Rome New York 13441-4505			10. SPONSORING / MONITORING AGENCY REPORT NUMBER  AFRL-IF-RS-TR-2005-311	
11. SUPPLEMENTARY NOTES  AFRL Project Engineer: Mark G. Alford/IFEA/(315) 330-3802/ Mark.Alford@rl.af.mil				
12a. DISTRIBUTION / AVAILABILITY STATEMENT APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.				12b. DISTRIBUTION CODE
13. ABSTRACT (Maximum 200 Words) This report documents work on an in-house effort that explored new mathematical and physical concepts to be applied to fusion. The beginning of the effort began with a broad-brush look at many new mathematics and physics lectures and papers. Much general literature searching eventually led to a focus on specific works that dealt with several new and unexplored areas of fusion research. The focus areas were in the following regimes: multi-tensor homographic computer vision image fusion, out-of-sequence measurement and track data handling, Nash bargaining approaches to sensor management, pursuit-evasion game theoretic modeling of fighter on fighter threat situation outcomes, and particle filtering. The main emphasis of the report is on particle filtering. The contribution is in part an accessible introduction to particle filtering which includes logical foundations and derivations of the fundamental prediction and update equations (Chapman-Kolmogorov and Bayes, respectively). Additionally the application of multi-tensor homographic fusion notions are identified together with the Nash approach, the pursuit-evasion approach to threat situation outcome determination, and the out-of-sequence measurement and track solutions.				
14. SUBJECT TERMS Particle Filtering, Non-Linear Processes, Non-Gaussian Processes, Computer Vision, Image Fusion, Homography, Quadrifocal Tensor, Trifocal Tensor, Out of Sequence Measurements, Out of Sequence Tracks, Nash Bargaining, Pursuit-Evasion Games, Threat Situation Outcome			15. NUMBER OF PAGES 40	
			16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT  UNCLASSIFIED	18. SECURITY CLASSIFICATION OF THIS PAGE  UNCLASSIFIED	19. SECURITY CLASSIFICATION OF ABSTRACT  UNCLASSIFIED	20. LIMITATION OF ABSTRACT  UL	

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## 1.0 INTRODUCTION

An explanation of the title of this effort, “Complementary Advanced Fusion Exploration (CAFÉ)” is in order at the outset. “Complementary” refers to the notion of supplementing and aiding the research in efforts directly related to improving the state of mathematical applications to fusion. These efforts are limited to those in the Fusion Technology Branch, and more specifically, those being monitored by the author. Some reference to a broader class of fusion problems may also be addressed in the development. “Advanced” refers to sets of problems and solutions not typically considered by fusion researchers. That is, The goal here is to “fill in some blanks” with respect to new ideas in sensor, data, information, and other forms of fusion. “Exploration” is not to be confused with “Exploitation.” This term refers to the notion of examining the mathematical, physical, and engineering literature, attending talks by foremost researchers, and keeping abreast of the most recent developments of those researchers. This has been the attempt of this author during this effort together with “out of the box” thinking.

The beginning of this effort dealt with examining specific archives of information, including the streaming video available from the Mathematical Sciences Research Institute (MSRI). Additionally <http://www.kitp.ucsb.edu/> online talks were of great use, as was the MIT Open CourseWare and other sources. These videos are considered extremely valuable and the reader is encouraged to explore them It also included a look at categories within arxiv.org and citeseer. At the end, the author was led back to PhD Theses, IEEE articles, SPIE articles, IEE articles, and Books available from the AFRL Technical Library.

As part of the effort, three summer students were hired to assist the engineer. The result of their work led to a look at Unmanned Aerial Vehicle Swarm Path Planning analysis, Kalman Filtering, Trifocal Tensor and Bundle Adjustment, and Game Theoretic research, and finally, particle filtering.

This report documents the work performed on an in-house effort entitled “Complementary Advanced Fusion Exploration.” The effort began with a thorough

canvassing of various mathematics and science literature to determine what new techniques could be applied to the area of Information Fusion. The result of this research led to a focus in the areas of particle filtering, force aggregation using Probability Hypothesis Methods (PHM), and Data Mining of Ground Moving Target Indicator (GMTI) Databases.

The overall objective of the effort was to complement existing and past efforts that have been applied to the Airborne Warning and Control System (AWACS), the Joint Strike Fighter (JSF), Multimission Command and Control Systems (MC2S), and Space Based Radar (SBR). MC2S includes both the Multimission Command and Control Aircraft (MC2A) and the Multimission Command and Control Constellation (MC2C).

Among these was an effort performed by Andro Consulting Service (ACS) that Dr. Donald Weiner, Dr. Pramod Varshney, and Dr. Ruixin Niu, all of Syracuse University at the time. Dr. Niu had written his thesis entitled Practical Issues in Target Tracking under the advisement of Dr. Yaakov Bar-Shalom and Dr. Peter Willett, of the University of Connecticut. The effort involved a trip to the AWACS System Program Office (SPO), to brief them on the idea of using AFRL's JVIEW Tool for the AWACS Block Upgrade being considered at the time. One of the things that came out of that meeting was the archaity of the AWACS Computing Capabilities. The idea was to improve the AWACS picture by enabling the AWACS to visualize weather as detected by onboard sensing equipment and discern targets in adverse environments. The ideas were all good but the effort did not proceed to Phase II due to funding limitations.

Other efforts that were capitalized upon included Phase I and Phase II SBIRs that were performed by Dr. Daniel H. Wagner's (DHW), C. Allen Butler, Dr. W. Reynolds Monach, and Scientific Systems Company Incorporated (SSCI). Dr. Ronald Mahler was the consultant on the SSCI effort. Dr. Butler teaches a course in Kalman Filtering. Dr. Monach was involved in developing non-Gaussian tracking algorithms that involved a Monte-Carlo approach. Several other areas were studied by DHW. These included a voice interface for the AWACS operator using ViaVoice, Decision Aids for the AWACS operator, bearings only tracking, Bayesian Networks for Combat Identification (CID), and Genetic Algorithm (GA) AWACS Flight Path Optimization (FPO). When the idea of GA-FPO was brought in front of the AWACS SPO, they basically indicated that it was

unlikely that the AWACS Crew would be receptive to altering their flight paths despite the potential increase in ground coverage area.

SSCI's work dealt with, among other things, Unified Bayesian Situation Assessment Sensor Management. They actually implemented a particle filter in their research. The most recent Phase I effort has proceeded to Phase II and offers promise in the area of Force Aggregation using Probability Hypothesis Methods.

In addition to the contractual small business efforts, two summer students were involved in conceptualizing research ideas. Richard Hartz did some UAV Swarm Path Planning research, and Melissa Neumann (ref. Appendix E) implemented Kevin Murphy's Kalman Filter and researched Game Theory Level III fusion, and Trifocal Tensor Estimation.

Most recently, the focus has been on particle filtering. There is a need to inform operational users of the Kalman Filter of the benefits of particle filtering.

The seminal paper on particle filtering is [2]. Another useful paper on particle filtering is [3]. This paper points out the increasing importance of including the elements of nonlinearity and non-Gaussianity. This is especially true in military applications where the world/environment is definitely not linear or Gaussian. In [3] seven particle filtering algorithms are described. These are as follows.

- Sequential Importance Sampling (SIS)
- Resampling Algorithm
- Generic Particle Filter
- Sampling Importance Resampling (SIR)
- Auxiliary Particle Filter
- Regularized Particle Filter
- "Likelihood" Particle Filter

Each of these particle filters has its own distinct advantages and disadvantages, spelled out in the paper.

## 2.0 PARTICLE FILTERING EQUATIONS

The following equations [2-4] are used in particle filtering (ref. appendix B).

$$p(x_k | z_{1:k-1}) = \int p(x_k | x_{k-1}) p(x_{k-1} | z_{1:k-1}) dx_{k-1} \quad (1)$$

$$p(x_k | z_{1:k}) = \frac{p(z_k | x_k) p(x_k | z_{1:k-1})}{p(z_k | z_{1:k-1})} \quad (2)$$

where we have used the notation  $z_{1:k}$  to denote the set of measurements  $\{z_i: i=1, \dots, k\}$ . This constitutes the available information at time step  $k$ . The first equation is the prediction step. Particle filtering uses Markov Chain Monte-Carlo (MCMC) method to draw a sample of the probability density function (pdf) of the system noise. It assumes that we have a set of random samples from the pdf of under the integral sign of (1), namely  $p(x_{k-1}|z_{1:k-1})$ . The particle filter propagates these samples according to (1) and then updates the samples according to (2) to obtain a set of values that are approximately distributed as  $p(x_k|z_{1:k})$ . Quoting from [2], during the prediction step: “Each sample is passed through the system model to obtain samples from the prior at time step  $k$ .” The system model referred to is the familiar:

$$x_k^*(i) = f_{k-1}(x_{k-1}(i), w_{k-1}(i)) \quad (3)$$

“where  $w_{k-1}(i)$  is a sample drawn from the pdf of the system noise  $p(w_{k-1})$ .” The function  $f$  is the system transition function that propagates the state vector  $x$  from time  $k-1$  to time  $k$ . During the update step, the measurement  $z_k$  is used to “obtain a normalized weight for each sample.” The normalized weight is denoted:

$$q_i = \frac{p(z_k | x_k^*(i))}{\sum_{j=1}^N p(z_k | x_k^*(j))} \quad (4)$$



where  $q_i$  is the “probability mass associated with element  $i$ .” This original particle filter was referred to as the “bootstrap filter.” It approximates densities by a finite weighted sum of  $N$  Dirac densities centered on elements of  $\mathbf{R}^n$  called particles [5].  $\mathbf{R}^n$  denotes real  $n$ -tuple space. That is, the space of  $n$ -tuples of real numbers (where  $n$  is a positive integer). It is an extension of the space  $\mathbf{R}^3$ . The space  $\mathbf{R}^3$  consists in the set of all real 3-tuples (all ordered sequences of three real numbers) with addition, scalar multiplication and the additive identity element  $(0, 0, 0)$  defined on the space as well as all the other requirements for a linear space.

### 3.0 GRID-BASED FILTERS

Grid-based filters use numerical integration for dynamic state estimation. They evaluate the pdf of the state over a grid in state space [2]. The assumption is that the state space is discrete and consists of a finite number of states [3]. The posterior pdf,  $p(x_{k-1}|z_{1:k-1})$ , is written as a weighted sum of delta functions. This weighted sum is then substituted into (1) and (2) to derive the prediction and update equations used, and the expression for the weights comes from making this substitution. The result is very similar to (4).

### 4.0 PROBABILITY HYPOTHESIS DENSITY (PHD) PARTICLE FILTERING

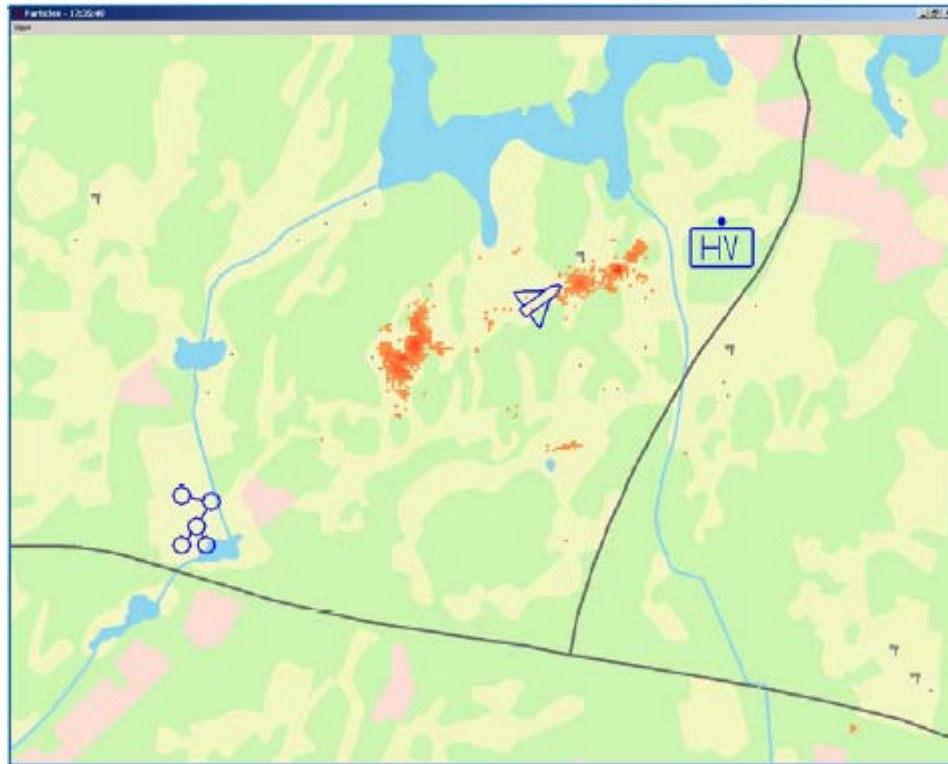
The Swedish Defense Research Agency is investigating the following Information Fusion Methods [7].

- Force Aggregation
- Tracking
- Sensor Resource Management

As part of that research they are focusing on analyzing intelligence reports at the division level in a ground warfare scenario. Their force aggregation approach involves clustering and classification. For ground vehicle tracking they are using a PHD Particle Filter. Their sensor resource management uses random set simulations.

They view the problem of tracking of a large number of vehicles in terrain

from incomplete observations as having the solution of PHD particle filtering. Figure 1 shows their implementation of this.



**Figure 1. Ground Target Tracking using Airborne PHD Particle Filter**

They track the first moment of joint distribution, i.e., PHD. The integral of PHD over an area is the expected # targets. This avoids combinatorial explosion and is therefore good for large number of vehicles. The particle filter implementation does not require analytical motion nor observation models and is suitable for non-linear problems.

SSCI has a Matlab implementation of a PHD-PF that they agreed to provide to Air Force Research Laboratory's Fusion Technology Branch. All that is needed is someone to take the Matlab code and implement it in the laboratory using real or more realistic data. This has the potential of improving tracker performance based on the fact that real data is generally nonlinear and non-Gaussian. Not only that, but the distribution of the system and measurement noise is usually an unknown, and the PHD-PF is able to handle system or measurement noise of any distribution.

## 5.0 PARTICLE FILTERING AND REAL DATA

The arena of particle filtering has grown since its inception in 1993. Acceptance Within the Air Force fusion community has been somewhat slow. There is a plethora of raw data to which particle filtering could be applied. A good next step would be to gather or acquire some real data and try various particle filters out. Clearly, the real world is nonlinear as well as non-Gaussian.

## 6.0 PARTICLE FILTERING: THE BASIC ALGORITHM

The basic algorithm for particle filtering as implemented consists of the following assumptions and steps. The first assumption is that the form of equation (3), hereafter referred to as the “formula”, along with a distribution of the noise is known. A major challenge is to come up with these initial assumptions. Kitagawa’s formula is the basic one used in the original paper [2], and in the tutorial [3]. There are several other formulas available from the economics literature. Another way to model this formula is to use the classic linear state transition function, but with the nonlinear control input maneuver models [22]. The form of equation (3) used in the Kalman Filter is well known to be

$$x_k = \phi x_{k-1} + B(u_{k-1} + w_k) \quad (5)$$

Where:

$$\phi = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

And

$$B = \begin{bmatrix} \frac{T^2}{2} & 0 \\ T & 0 \\ 0 & \frac{T^2}{2} \\ 0 & T \end{bmatrix}$$

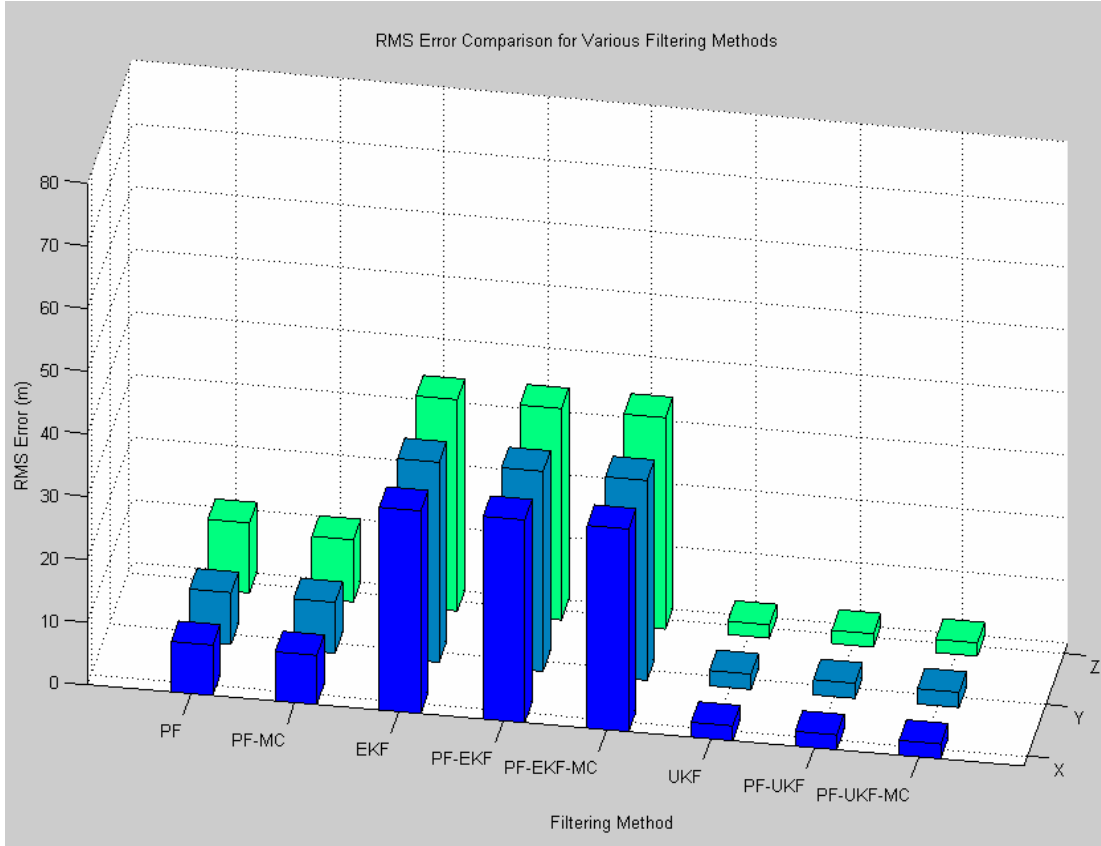
Also  $u$  and  $w$  can be treated as the acceleration and noise models of the target. That is  $u=(a_x, a_y)$ .

Getting back to the basic algorithm, the predicted state is simply an implementation of equation (3), with a sample from the desired noise distribution added. This is followed by a calculation of the importance weights which begins with a calculation of the likelihoods for the particles. The likelihood used in [23] is as follows:

$$w_t^{(i)} = \frac{1}{\sqrt{\sigma}} \exp \left[ -\frac{1}{2\sigma} (y - y_{pred}^i)^2 \right] \quad (6)$$

It was normalized by dividing each weight by the sum over  $i$  of the all the weights. One of three resampling techniques (residual, systematic, or multinomial, are then applied, and the time for the total calculation is computed. This enables an evaluation of performance versus resources.

In the results obtained in-house, the Unscented Kalman Filter outperformed the basic PF algorithm, and the Unscented Particle Filter (UPF) did the best (ref. fig. 2).



**Figure 2. Results of in-house analysis, showing superior performance of UPF.**

## APPENDIX A - DENOMINATOR OF SECTION 1 EQUATION 2

The denominator of Equation (2) is comes from the Total Probability Theorem (TPT) and is given by

$$p(z_k | z_{1:k-1}) = \int p(z_k | x_k) p(x_k | z_{1:k-1}) dx_k \quad (\text{A1})$$

Giving

$$p(x_k | z_{1:k}) = \frac{p(z_k | x_k) p(x_k | z_{1:k-1})}{\int p(z_k | x_k) p(x_k | z_{1:k-1}) dx_k} \quad (\text{A2})$$

This comes from the more familiar form of Bayes' Theorem, from

$$P(A_i | A) = \frac{P(A_i)P(A | A_i)}{\sum_{j=1}^N P(A_j)P(A | A_j)} \quad (\text{A3})$$

It should be recalled that the TPT applies to mutually exclusive events. The TPT states that the denominator of equation (A3) is equal to  $P(A)$ . The mutually exclusive events are the  $A_j$ 's.

## APPENDIX B – MEASUREMENT TIME UPDATE FROM BAYES RULE AND THE TOTAL PROBABILITY THEOREM

Here is the derivation of equation (2), starting from Bayes' rule.

$$P(A | B) = \frac{P(AB)}{P(B)} \quad (\text{B1})$$

$$P(B | A) = \frac{P(AB)}{P(A)} \quad (\text{B2})$$

Solving for  $P(AB)$  in equations (B1) and substituting the result into equation (B2) yields the following equation.

$$P(B | A) = \frac{P(B)P(A | B)}{P(A)} \quad (\text{B3})$$

The total probability theorem states the following.

$$P(A) = \sum_{i=1}^N P(B_i)P(A | B_i) \quad (\text{B4})$$

Substituting this into equation (B3) yields the following equation.

$$P(B | A) = \frac{P(B)P(A | B)}{\sum_{i=1}^N P(B_i)P(A | B_i)} \quad (\text{B5})$$

Let  $B=x$  and  $A=z$ .

$$P(x | z) = \frac{P(x)P(z | x)}{\sum_{i=1}^N P(x_i)P(z | x_i)} \quad (\text{B6})$$

Rewrite this as follows.

$$P(x | z) = \frac{P(z | x)P(x)}{\sum_{i=1}^N P(x_i)P(z | x_i)} \quad (\text{B7})$$

Letting the summation become an integral.

$$P(x | z) = \frac{P(z | x)P(x)}{\int P(x)P(z | x)dx} \quad (\text{B8})$$

Let  $x=x_k$  and  $z=z_k$ .

$$P(x_k | z_k) = \frac{P(z_k | x_k)P(x_k)}{\int P(x_k)P(z_k | x_k)dx_k} \quad (\text{B9})$$

Let  $P(x_k) = P(x_k | z_{1:k-1})$ .

$$P(x_k | z_k) = \frac{P(z_k | x_k)P(x_k | z_{1:k-1})}{\int P(x_k | z_{1:k-1})P(z_k | x_k)dx_k} \quad (\text{B10})$$

Rewriting this as follows.

$$P(x_k | z_k) = \frac{P(z_k | x_k)P(x_k | z_{1:k-1})}{\int P(z_k | x_k)P(x_k | z_{1:k-1})dx_k} \quad (\text{B11})$$

Let  $P(x_k | z_k) = P(x_k | z_{1:k})$ .

$$P(x_k | z_{1:k}) = \frac{P(z_k | x_k)P(x_k | z_{1:k-1})}{\int P(z_k | x_k)P(x_k | z_{1:k-1})dx_k} \quad (\text{B12})$$

This is in now the form of equation (2).

## APPENDIX C – CHAPMAN KOLMOGOROV EQUATION

Here we are basically using a transitive property of integrating probability density functions.

$$p(x_A | x_C) = \int p(x_A | x_B) p(x_B | x_C) dx_B \quad (C1)$$

This easily translates to equation (1). Markov chains are sequences of random variables in which the future variable is determined by the present variable but is independent of the way in which the present state arose from its predecessors.

## APPENDIX D – WEIGHTED SUM OF DELTA FUNCTIONS

The main idea of a particle filter is to approximate  $p(x_k/z_{1:k})$  with a sum of Dirac Delta functions located at the samples  $x_k(i)$ .

$$p(x_k | z_{1:k}) \cong \sum_{i=1}^N q_i \delta(x_k - x_k(i)) \quad (D1)$$

Where the  $q_i$  weights are valid at the  $k^{\text{th}}$  time step and are given by equation (3).

## APPENDIX E – IDEAS FOR NETWORKED SENSOR MANAGEMENT

### Ideas Presented for Networked Sensor Management

*Melissa Neumann: Mechanical Engineering Undergraduate; Binghamton University*

*In conjunction with Mark Alford (Mentor): AFRL/IFEA*

#### **Acknowledgements:**

*Thanks to Mark Alford and Andrew Noga (IFEC) for all your help.*

**Abstract** The theory of data fusion has become important to military applications and in particular, tracking applications. Discussed are possible tracking processes for each of the first three levels of data fusion. An introduction to data fusion and the different levels are included.

#### **Introduction to Information Fusion**

“Data Fusion is a process dealing with the association, correlation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates for observed entities, and to achieve complete and timely assessments of situations, threats and their significance.

The process is characterized by continuous refinements of its estimates and assessments, and by the evaluation of the need for additional sources, or modification of the process itself, to achieve improved results.” JDL DFG 1992’ (10)

### **Level 1 Fusion: Object Refinement**

“Observation-to-track association, continuous state estimation (e.g. kinematics), discrete state estimate (e.g. target type and ID) and prediction.” (10)

### **Level 2 Fusion: Situation Refinement**

“Object clustering and relational analysis, to include force structure and cross force relations, communications, physical context, etc.” (10)

### **Level 3 Fusion: Impact Assessment**

“[Threat refinement]: threat intent estimation, [event prediction], consequence prediction, susceptibility, and vulnerability assessment.” (10)

### **Levels 0, 4, and 5 Fusion:**

Level 0: Sub-object data association and estimation.

Level 4: Process refinement (resource management).

Level 5: Human/computer processing.

### **Discussion of Ideas for Levels 1 through 3 Information Fusion**

#### **Level 1 Object Refinement**

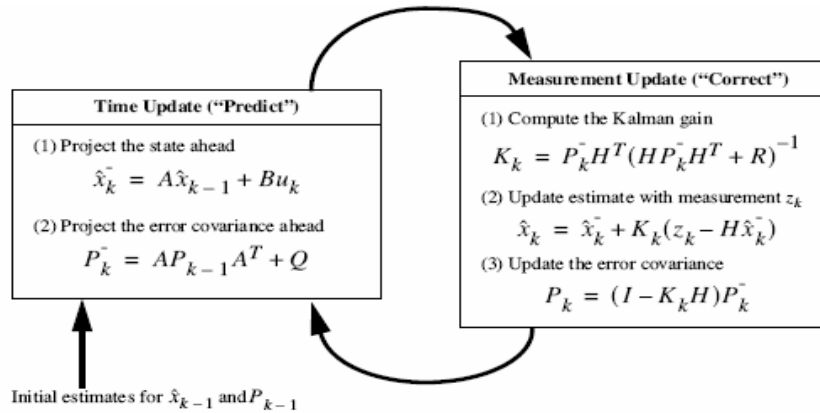
The Kalman Filter has been widely used for information fusion applications. This dynamic estimation algorithm has had many filters modeled after it.

“The Kalman filter addresses the general problem of trying to estimate the state  $x \in \mathbb{R}^n$  of a discrete-time controlled process that is governed by the linear stochastic difference



equation  $\hat{x}_{k+1} = A_k \hat{x}_k + B u_k + w_k$  with a measurement that is  $z_k = H_k \hat{x}_k + v_k$ .

([http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL\\_COPIES/WELCH/kalman.1.html](http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/WELCH/kalman.1.html))



**Figure 4.2:** A complete picture of the operation of the Kalman filter, combining the high-level diagram of Figure 4.1 with the equations from table 4.1 and table 4.2.

[http://www.cs.uns.edu/~tracker/media/pdf/SIGGRAPH2001\\_CoursePack\\_08.pdf](http://www.cs.uns.edu/~tracker/media/pdf/SIGGRAPH2001_CoursePack_08.pdf)

## MATLAB for Kalman Filtering

During summer of 2004 research, potential MATLAB solutions were found for Kalman Filter tracking applications. A working example of the Kalman Filter for MATLAB was found as free software. The software can be implemented to various degrees for target tracking. It is also possible to modify the software for simple to medium complex situations. *Author: Kevin Murphy, 1998, Affiliation: MIT Artificial Intelligence Laboratory.* <http://www.ai.mit.edu/~murphyk/software/kalman/kalman.html>

In addition to this software, a valuable resource was the text “Estimation with Applications to Tracking and Navigation” by Bar Shalom, et al. Bar Shalom and colleagues discuss what is called the IMM or Interacting Multiple Model estimator. This IMM is based on the Kalman Filter. “In the *interacting multiple model (IMM) estimator*, at time  $k$  the state estimate is computed under *each possible current model* using  $r$  filters,

with each filter using a different combination of the previous model-conditioned estimates- *mixed initial condition.*” (11)

The use of the IMM estimator could be applied easily to ATC (air traffic control) tracking and estimation. Bar Shalom discusses this application in two modes of flight- uniform motion and maneuver. Results received from a sample problem in the text were as follows:

“The KF is clearly inferior to any (reasonably designed) IMM estimator. The accuracy of the turn rate estimate is not very important as far as the quality of the position, speed, and course estimates are concerned. What is important is the correct and timely detection of the maneuver and the fast response of the filter to his direction. The IMM-CT estimator is the best choice for tracking maneuvering with its capability to track the linear as well as turn motion of the target.” (11)

Future exploration on the topic of level 1 fusion would include using the combined knowledge of Kalman filtering and IMM estimators. Using this knowledge, one can develop software using Kevin Murphy’s Kalman Toolbox and Bar Shalom’s, et al DynaEst (a MATLAB program developed for the IMM) to perform accurate and fast tracking estimations for ATC applications.

### **Level 2 Situation Refinement**

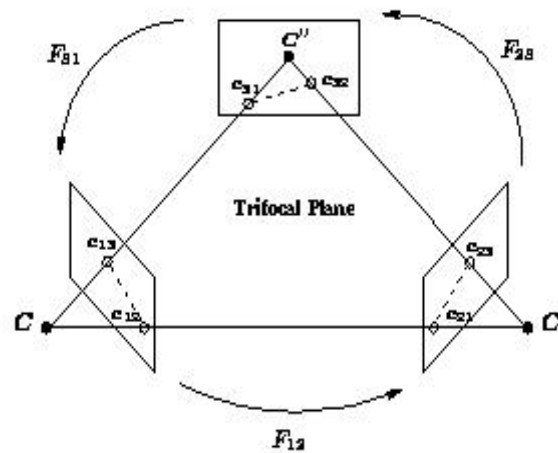
The approach for level 2 fusion was researching multi-image fusion. The text “Multiple View geometry in Computer Vision” by R. Hartley and A. Zisserman was the primary source of research. Research was concentrated on Trifocal Tensor Estimation and Bundle Adjustment. The goal was to find an appropriate model to develop 3D reconstructions from 2D images and identify targets using the retrieved images.

Trifocal tensor estimation uses multiple 2D images and tensor algebra to form a 3 dimensional result.

Example:

- Obtained 3 separate images of the same object at 3 slightly different angles.
- Fundamental matrices may not always work when reconstructing the images into a scene.
- Need to estimate 3 projections at once.
- Deployment of a trifocal tensor can be used for this process where each “camera” view is related by a fundamental matrix.

Trifocal tensors, along with fundamental matrices, can be very useful in computer vision when building 3D images from large sequences of images (20 or 30 or more). (12) The following figure shows the basic construction of the trifocal plane.



Trifocal tensor algebra is complicated, but it can be used to fuse many images retrieved from networked sensor equipment. Possible types of networks this could be used in are Multi-UAV with ground control, UAV to ground, Multi-Aircraft, etc.

Bundle adjustment is even more complicated, but may be more accurate when reconstructing into 3 dimensions. “Bundle adjustment is the problem of refining a visual reconstruction to produce *jointly optimal* 3D structure and viewing parameter (camera pose and/or calibration) estimates. *Optimal* means that the parameter estimates are found by minimizing some cost function that quantifies the model fitting error, and *jointly* that the solution is simultaneously optimal with respect to both structure and camera variations.” (13) This obviously would have more complicated mathematics than trifocal tensor estimation. However, the capability to account for error could be of more use for military applications than trifocal tensor estimation.

### **Level 3 Impact Assessment**

This is one of the most important, and difficult to find solutions for, levels of fusion. It is very important to target tracking since it is difficult to know what an enemy vehicle or even friendly vehicle may do. Past attempts have shown that impact assessment can be complicated to implement or to develop algorithms. The majority of research for all levels of fusion have been concentrated on impact assessment more recently because of this.

The proposed solution researched over the summer of 2004 and continued from 27 December 2004 to 21 January 2005 is *Dynamic Game Theory*. Game theory has become extremely popular for evolutionary AI purposes. Most of the purposes allow AI programs to “evolve” as they work. However, not much research has been performed with respect to level 3 fusion. One first has to have a basic knowledge of game theory and realize that impact assessment in an air combat “game” is not a cooperative one as well as being dynamic. This basic knowledge makes the available text more understandable.

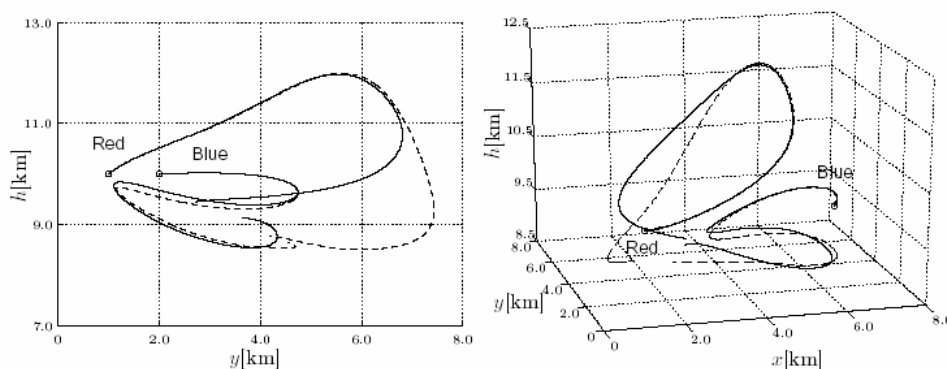
## Summer Research

There has been research performed in the area of combat games by few researchers. Pursuit evasion games have had text available since the “acknowledged father of pursuit evasion games,” R. Isaacs, published “Differential Games” in 1965. In pursuit evasion games, the time duration of the game is not fixed. Basar and Olsder discuss pursuit evasion games in their text, “Dynamic Noncooperative Game Theory.”

(14) A game of this type uses simple kinematics but complicated game theory mathematics to calculate the “threat” of a target by evaluating whether a vehicle is in pursuit or evasion. If this process was combined with target tracking via Kalman Filtering techniques and multi-view geometry, it would give more accurate threat assessments.

Conclusions during the summer showed that more basic game theory analysis may be used to assess threat using Kalman filtering and multi-view geometry retrieved information. Sensor management could be carried out in such a way that certain sensors hold precedence over others in certain situations. This would be controlled through Nash Bargaining theory.

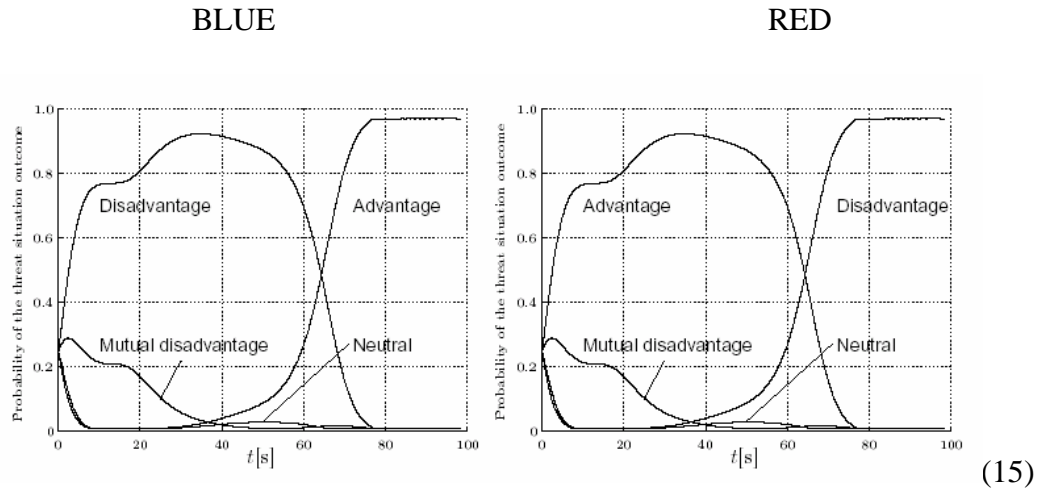
An example of an air combat game is shown below.



(15)

This pursuit evasion game involves red and blue forces. The game model offers a novel way of analyzing optimal air combat maneuvering and to develop automated decision making system for selecting combat maneuvers.

The following figure allows one to see who gains or loses the competitive advantage over time in the above game.



Level 3 fusion can be accomplished by plotting the probability of the threat situation outcome as a function of time. Game theory aids us in performing important tasks in level 3 fusion.

## Winter Research

### Pareto Optimality

The idea of *pareto optimality* is widespread in game theory. The concept is defined as a way to make at least one “player” of a game better off without making any other “player” worse off than they were. This is an obvious plus for air force or other military applications. To better understand what this means, an example follows. Given a group of ground vehicles and one aircraft, if the aircraft has the optimal field of view of a target, the aircraft controller could then send information to the ground vehicles and

therefore no one on what can be called the blue team will be at more of a disadvantage than they would have if the target (or red team) information was not known. This is a very basic example, but it is possible to broaden the idea to complicated situations such as where multiple UAV's are present and information is needed on whether or not one particular UAV is transmitting more important information than another.

In the presence of a combat “game,” impact assessment must be maintained in order to decide what is optimal. By combining a pursuit evasion game to predict positions of targets and a pareto optimality strategy, one can assess the threat of the target in addition to which “blue” vehicle should hold precedence when tracking the target.

### **Group Target Tracking**

Sadjadi and Kober (16) discuss group target tracking using game theory in terms of state vectors and game theoretic *leader-follower* strategies. Assumptions are made that object are members of one single group and their state vectors are affected by terrain topography and group-membership requirements. To determine a group, a matrix can be set up using x, y, and z (when needed) axes with the velocity vector projection associated with a different target in each row. By finding the covariance associated with the velocity matrix and finding the eigenvalues, one can see whether or not the targets are moving in the same direction and consequently, if they belong to the same group. Likewise, the eigenvectors of the covariance matrix can show the general direction that the group is moving.

It is discussed that if the eigenvalues are both distinct, that 2 situations may be occurring. One is that the group is splitting into two groups and moving separately. The second is that the group remains as one but the terrain is causing a sequential path change

of parts of the group to be curved. The leader-follower model later discussed deals with combining the eigenvalue analysis with the model.

The leader-follower model is exactly how it sounds. There will almost always be a “leader” of a group and each individual object will follow that leader. Because of this, game theoretical computations can be made directed towards the state of the group. This all comes back to the IMM estimator discussed previously. Worth mentioning is the fact that in order to properly use this group target tracking technique, there must be certain control laws assigned to group members that are used to preserve group membership. In other words, there must be a leader and there must be a follower.

### **Grocholsky Thesis**

Ben Grocholsky of the University of Sydney has written a thesis based on multi-sensor, multi-vehicle systems. The thesis discusses “principles and architecture developed for decentralized data fusion and sensor management.” (19) Grocholsky mainly discusses the autonomous operation of robotic systems and how they collectively work together towards a common goal via sensor management. However, the same logic can be applied to human operation. The best way to explain the thesis is to simply quote the author.

- Chapter 2 considers approaches to distributed multi-robot systems. Conventions used through the thesis are stated. These include definitions of coordination, cooperation and the characteristics of decentralized systems. The formulation of the team decision problem is presented and its connection to the Nash bargaining problem is established. An iterative procedure known as better-response negotiation is introduced as a means for determining Nash equilibria. Key elements in engineering decentralized decision making team members are identified as: modeling of the environment, sensors and vehicles; specification of communication structures; capturing team utility; parameterization of actions and devising solution procedures.
- Chapter 3 covers the problem of quantifying and fusing information in multi-sensor systems. Information is formally defined, in terms of uncertainty, by Fisher



and Shannon measures. The Information filter is presented as a mechanism for scalable decentralized fusion of data from multiple sources. The manner in which information is lost and gained in the fusion process is discussed and quantified. Entropic and mutual information are determined to be appropriate expected utility measures for sensing actions. Common information among observations is identified as the source of coupling in team utility derived from entropic information. The decentralized data fusion process and information-theoretic utility structure are identified as forming a consistent basis for gathering, exchanging, evaluating and fusing information in the team decision problem. The approach is demonstrated through the analysis of a discrete sensor assignment problem.

- Chapter 4 presents information gathering as an optimal control problem. Modeling of the environment, vehicles and sensors is combined with utility based on entropic information. This is applied to the determination of optimal information seeking trajectories for the case of a single bearings-only sensor platform localizing a point feature. The implications of this example for active sensing tasks is explored and discussed. Consideration then turns to problems involving multiple sensor platforms. Attention is focused on the team utility structure and its role in cooperation. A proposed decomposition of the team utility is used to explore the influence of coupled utility on the optimal member decisions. This identifies relationships between the optimal individual and team solutions with implications for the complexity of the cooperative solution. A localization example with two range-only sensors is used to illustrate these results. It is then demonstrated that the optimal team solution can be determined through a better-response negotiation procedure.
- Chapter 5 explores communication and coupled utility among decision makers as fundamental mechanisms underlying coordination and cooperation. Propagation of observation information through the decentralized data fusion process leads to coordination by altering the prior information on which local decisions are based. The individual decision making processes become coupled when propagation of expected observation information is permitted. This enables determination of the cooperative team solution by negotiation. Coordinated and cooperative solutions are demonstrated through extension of the single vehicle bearings-only example from Chapter 4 to multiple sensor platforms and features. The applicability of this approach to other tasks is demonstrated through an area exploration problem. Finally, all the elements considered through this are brought together to form a general architecture for decentralized coordinated control of multi-sensor information gathering systems.
- Chapter 6 presents the main conclusions and identifies a range of future research directions for the work described in this thesis. (19)

As one can see, this is a direct approach to the difficulty of data fusion. Level 3 fusion is once again discussed in a manner of game theory using the Nash bargaining problem approach. The optimal control problem discussed is representative of level 3

fusion, also. This refers to the idea that one sensor may hold precedence over all others due to information being gathered showing more importance. Overall, the thesis discusses novel ways to approach data fusion using optimal control theory and information-theoretic techniques. These are highly relevant techniques, especially for multi-UAV systems.

### **Particle Filtering** (also discussed by Mark Alford)

The method of particle filtering is a Bayesian state estimate based system for nonlinear/non-Gaussian problems. One of the most popular approaches to the problem is using the EKF (extended Kalman filter). However, this approach still requires a Gaussian PDF (probability density function) at every iteration. This is an issue because the nonlinear/non-Gaussian PDF is not a general closed form expression. Gordon, et al (17) discuss other methods that have been attempted. Presented is a filter labeled the “bootstrap” filter with implement a recursive Bayesian filter.

The main idea is to represent the PDF as a set of random variables rather than as a function. Since a large number of samples can be obtained, accuracy can be optimal. Without becoming overindulged in the mathematics, it should be said that particle filtering methods prove to be accurate against other filters. (18) Several types of particles filters have been developed, including a grid-based filter which is based on a numerical integration method, all seem to show improved outcome over the next best, EKF.

If these techniques are applied to game theory for level 3 fusion, one may find that the accuracy of impact assessment will increase. The method can be compared to the group target tracking discussion. If the same system is applied here but using a particle filter, it may be seen that the accuracy will increase tremendously over using a simple

Kalman filter technique. This is so because most real life situations in target tracking are nonlinear and non-Gaussian which particle filters take into account.

### **Mahler's Force Aggregation**

Ronald Mahler of Lockheed Martin Tactical Systems has developed a unified approach to force aggregation, or level 2 data fusion.(20,21) This approach is similar to the particle filtering technique described above using a recursive Bayesian filter. Mahler applies the filter to a multi-sensor, multi-target group. However, instead of the PDF being used, Mahler uses the probability hypothesis density (PHD). The aforementioned particle filtering only deals with continuous target groups, however, and not with situations where parts of the group may separate.

Mahler discusses equations involved with his recursive filter and compares it to others. He introduces the random cluster process with reference to group tracks. This is so because there are in affect, three layers to the group tracking process- a "twice-hidden group target layer," "a single-hidden layer," and a "visible observation layer." There is an underlying "mother process" which consists of finite definitions. In simple terms, the total statistical representation of a multi-sensor, multi-group system can be defined as a random finite subset.

It is shown that Mahler's process is accurate for state estimation with regards to level 2 data fusion. However, the assumption should be noted about the need that there should be an approximation strategy due to the generalization of the PHD. This is because the multi-sensor, multi-group Bayes filtering equations defined by Mahler are computationally expensive.

## **Closing Statement**

Much information was collected that could potentially create ease of data fusion in the future. There are many options open for level 3 fusion. These ideas should be investigated further so as to build a strong foundation for impact assessment. Together with the research found building levels one and two fusion, impact assessment can be accurately detected.

## **APPENDIX F – WORK PLAN FOR IN-HOUSE RESEARCH**

# **WORK PLAN FOR IN-HOUSE RESEARCH**

## **DEVELOPMENT AND EVALUATION OF FUSION TECHNIQUES (DEFT)**

Mark Alford x3802      Eric Jones x4410      Adnan Bubalo x2991

### **Introduction**

The Development and Evaluation of Fusion Techniques (DEFT) in-house program has multiple purposes. These purposes will be elaborated in Part I and Part II below. This effort is providing manpower only to establish an in-house program in fusion. A brief introduction to the DEFT program is as follows:

The first purpose of DEFT is to extend the development of algorithmic concepts that were identified and explored under the Complementary Advanced Fusion Exploration (CAFÉ) in-house program. CAFÉ investigated promising recent innovations, primarily involving mathematical concepts within the area of basic research, and did a preliminary assessment of their validity as well as a preliminary qualitative assessment of each concept's potential for application to Air Force Command, Control, Intelligence, Reconnaissance, and Surveillance (C2ISR) capabilities and systems. DEFT will also continue the investigation of potential exploratory development applications of the CAFÉ algorithmic concepts. In addition, DEFT will also investigate concepts that are revealed as extensions of the original CAFÉ concepts.

The second purpose of DEFT is to investigate additional concepts that were not originally investigated under CAFÉ for their exploratory development potential. Many concepts have been developed, particularly through the Small Business Innovation Research (SBIR) program. Often, these concepts are developed to show basic feasibility and validity of the concepts without fully investigating their exploratory development potential for application to Air Force C2ISR capabilities and systems. DEFT will examine three such areas which appear to have this exploratory development potential. In addition, DEFT will examine other concept areas of this type as they are identified.

DEFT will be accomplished in a systematic manner. This will include extensive use of existing publications. Concepts will be further investigated through mathematical verification as required, mathematical development as required, and incorporation into

and exercising of computer simulations. Limited creation of code will be pursued when necessary to support the simulation process. Documentation will be accomplished through periodic technical memos and reports as well as through the development of papers for journals and/or symposia as opportunities present themselves and when results justify it. Concepts that are fully developed, verified, and that show potential for useful Air Force C2ISR exploitation will be further developed and presented to potential funding sources for further formal exploratory development efforts and other types of technology transition.

## **Part I: CAFÉ Extensions**

As stated in the introduction, DEFT will extend the development of algorithmic concepts that were identified and explored under CAFÉ. CAFÉ investigated a number of promising recent innovations, a number of which are described below.

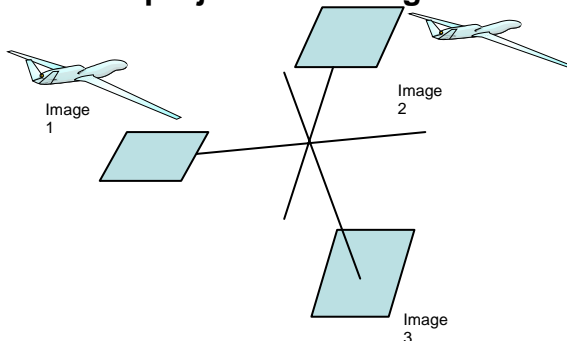
This part of DEFT will complement existing and new fusion research arenas. It will explore new technologies to complement work done in past and on-going contracts. A framework for past, existing and future efforts will be provided.

In addition, this part of DEFT will involve exploration of new mathematical and physical areas, concepts and ideas to apply to fusion technology. A major focus will be to review the most recently published papers to determine which ones have the most application to information fusion. Higher level mathematical constructs will be documented for later application to specific fusion challenges. New fusion concepts will be investigated. Mathematical models will be examined and refined for application to real world problems.

Research focus will initially be directed towards a number of the concepts explored under CAFÉ. These include:

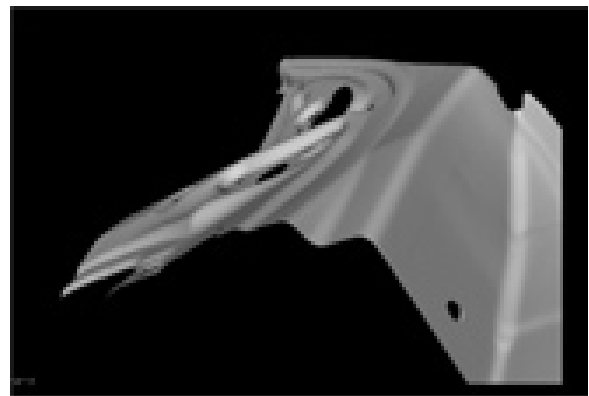
### **- Tensors (including Homography)**

**Trilinear tensors are used for reprojection of images**



Reprojection is taking an image and *reprojecting* (aka warping, remapping) it to a more useful map coordinate system.

**Tensors: Potential Payoff**



<http://www.cognitens.com/pages/Products.asp?intGlobalID=48>

## Nash (Grocholsky) Approach

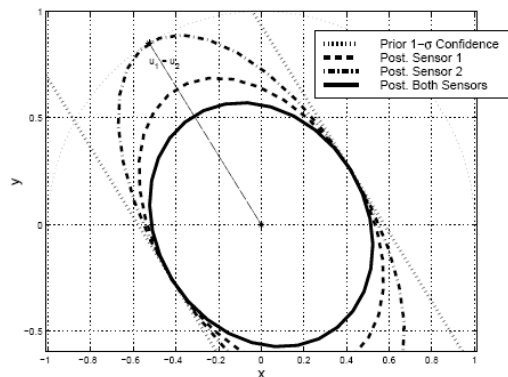
### Nash Equilibrium Approach to Sensor Management

What allows a collective of distributed autonomous decision makers to work together toward a common objective? The problem of seeking, sensing, interpreting perceptual information and interacting with other decision making elements in an inherently uncertain environment is a complex, and, as yet, unsolved problem.

A team consists of multiple decision makers. Each decision maker must make a decision that accounts for the decisions made by other members of the team. The team decision problem is to find optimal decision rules for each member so that the expected utility (payoff) of the whole team is maximized.

This cooperative situation falls under the general category of bargaining problems defined by Nash. It is a situation where individuals take actions associated with a set of outcomes. Each individual desires to maximize their gain from a bargaining process. The individuals are able to accurately compare preferences. The exchange is cooperative in the sense that individuals are able to discuss and agree on a joint plan of action.

### Nash Approach Payoff



From Grocholsky's Thesis

Considerations:

What do we do when the platforms do not exchange information?

How do we handle situations when there are conflicts between the sensors?

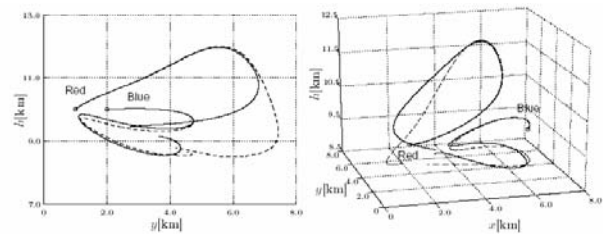
## - Virtanen Approach

### JSF pursuit evasion game



Applies to other scenarios as well

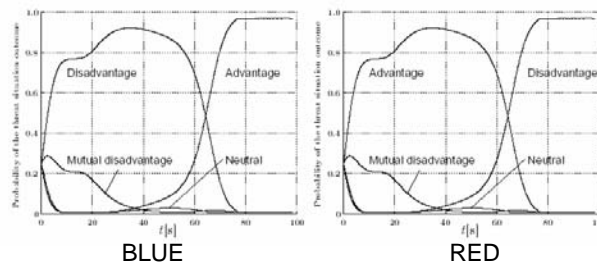
### Air combat modeling



Pursuit-evasion situation involving red and blue forces

This model offers a novel way to analyze optimal air combat maneuvering and to develop an automated decision making system for selecting combat Maneuvers.

### Virtanen Methodology Payoff



Gaining a competitive advantage: Level III fusion can be accomplished by plotting probability of threat situation Outcome as a function of time.

## - OOSMs, OOSTs

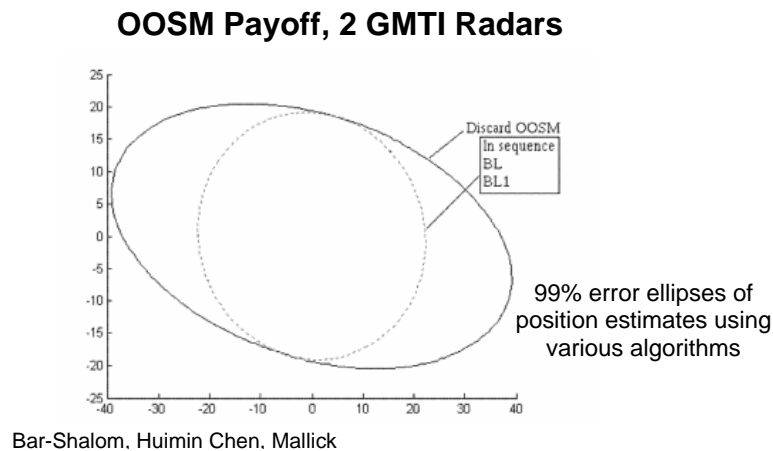
### Out of Sequence Problem (OOSP)

Most Information Fusion Filters assume sequential information arriving in a particular order. In many cases, in the real world, data (measurements, tracks, etc.) arrives out of order or out of sequence. Several papers address this problem, one being the thesis by Keshu Zhang. In her thesis, Keshu uses Best Linear Unbiased Estimation (BLUE) Fusion. She addresses the problem of how to update state estimates with Out of Sequence Measurements (OOSM). She also addresses how to apply the OOSM update algorithm to multiple targets in clutter



## OOSM Updating

Suppose there is no storage constraint. Then the OOSM update problem can be simply solved by rerun the Kalman filter with all data from the OOSM occurrence time to its arrival time. Bar Shalom first derived the OOSM update algorithm for the one-step delay problem.



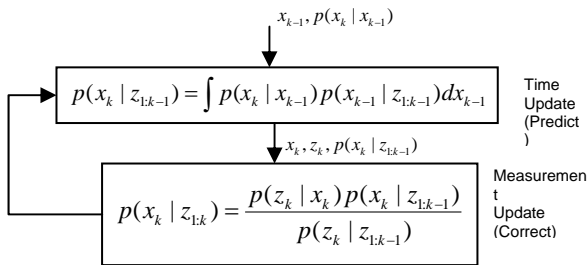
## - Particle Filters (PF)

Overcomes Gaussian and Linear assumptions of the Kalman Filter. It is based on the Chapman Kolmogorov Equation (prediction) and Bayes Theorem (update). PF models the target states as a sum of weighted delta functions (particles). Particle weights are computed from samples of a Monte Carlo distribution.

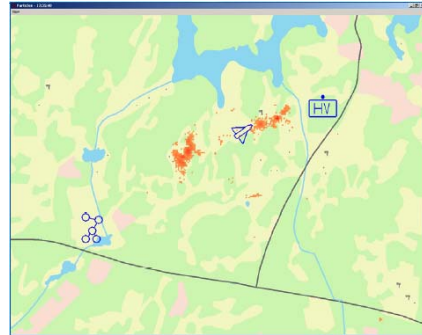
New variants of the basic bootstrap PF are being developed almost daily. Examples include: Sequential Importance Sampling, Re-Sampling, Generic PF, Sequential Importance Re-sampling PF, Auxiliary PF, Regularized PF, Likelihood PF, and PHD PF.

These are but a few of the growing number of approaches. Goal of current research is to review the various algorithms and get a basic understanding of the PF process. Efforts are underway by researchers to combine Identification and PF track fusion and also to develop a basis for assigning particular PF algorithms to particular types of real world problems.

## Time and Measurement Update



## Ground Target Tracking Using an Airborne Particle Filter



J. Schubert, C. Mårtensson, H. Sidenbladh, P. Svenson, J. Walter, "Methods and System Design of the FOI Information Fusion Demonstrator – IFD03," ICCRTS 9<sup>th</sup> International Command and Control Research and Technology Symposium September 14-16, 2004, Copenhagen, Denmark.

## Payoff of PF Compared to EKF

From tutorial by Arulampalam

Algorithm	Proposal	Section	Figures	RMSE
Extended Kalman filter	N/A	IV-A	3,4	23.19
Approximate grid-Based Filter	N/A	IV-B	5	6.09
SIR Particle filter	$p(x_k   x_{k-1}^i)$	V-B.1	6	5.54
Auxiliary Particle filter	$p(x_k   x_{k-1}^i)$	V-B.2	7	5.35
Regularised Particle filter	$p(x_k   x_{k-1}^i)$	V-B.3	8	5.55
'Likelihood' Particle filter	$p(x_k   s_k) p(s_k   z_k)$	A	9	5.30

Likelihood PF has lowest Root Mean Squared Error 5.30 as compared to 23.19

## - Other Topics

More topics will be discovered and pursued during this effort.

Some new ideas that could be pursued in this in-house effort would be:

- PF Track error – variation from classic ellipsoidal error
- General error & volume track shape error measurement
- Particle clustering
- S/W to test PFs for air-space-ground-sea
- Unclassified PF testbed with high computational speeds/storage capacity

## **Part II: Other Exploratory Development Topics**

As stated in the introduction, DEFT will also investigate additional concepts that were not originally investigated under CAFÉ for their exploratory development potential. Three concepts will be investigated; however this will not preclude the investigation of other new concepts that are identified. The first is an examination of the potential for advances in the exploitation of Bayesian Networks. The second is an examination of ways to exploit techniques that allow for a faster determination of optimized routes for Intelligence, Surveillance, and Reconnaissance (ISR) platforms. And the third is an examination of the possibilities for improved ISR capabilities through exploitation of Radio Frequency (RF) Tag technology, Unattended Ground Sensor (UGS) technology, and other associated techniques.

This part of DEFT shall integrate the use of analysis of concepts that have been developed through the study of past results, extension of more general analytic results for use in applications of interest, and simulation of concepts to investigate the utility of legacy and developed concepts. Investigation of the potential for these concepts is anticipated to yield reasonably specified variations that can be identified for further potential exploitation through more formal Exploratory Development activities. A further description of the three principal concepts under this part of DEFT is as follows:

### **- Bayesian Network Exploitation for Fusion**

Bayesian Networks have been in use for a number of years now. Perhaps the largest area of their use had been in the area of target identification and discrimination. More recently, they have been used more directly in support of multi-sensor fusion. These recent applications have been showing increasing innovation in the expansion of the ways in which Bayesian Networks can be used in support of fusion.

Among the areas that have been using Bayesian Networks in these ways, the Missile Defense Agency (MDA) is using Bayesian Networks as the basis for their Decision Architecture within Project Hercules. In addition, two recent SBIR efforts have used them as a means for multi-sensor fusion, in one case to fuse data that includes features derived from the concept of invariants, and in another as a basis for accomplishing distributed fusion. Another SBIR effort used a Bayesian Network in association with a Multiple Hypothesis Tracker (MHT) as a basis for target classification after target detection and tracking had been accomplished through the MHT. Through careful examination of the various ways that Bayesian Networks have been used in these and other efforts and studies, it is anticipated that new applications for them can be determined.

## **- Optimization of ISR Platform Route Determination**

Trying to optimize the sensor tasking process for the improvement of ISR performance for missions of interest is an area that has attracted much research interest in recent years.

One approach has been to try to optimize coverage through detailed up front planning, usually in coordination with the Air Tasking Order (ATO) process. This process is somewhat slow but allows for detailed planning that can utilize a large amount of optimization. However, changing these plans based on short term contingencies is difficult without doing great damage to the overall plan.

On the other hand, you can have a much shorter planning window. This, however, while it makes it easier to allow for short-term contingencies, results in overall plans that are considerably less optimal.

Recent efforts have approached this problem from both directions. The Advanced ISR Management (AIM) program is a Defense Advanced Research Projects Agency (DARPA) program that approaches the problem through the idea that the coming generation of collection systems will provide dramatically increased volumes of higher fidelity data to the operational decision-maker. AIM then proceeds under the idea that the challenge will be to dynamically manage and synchronize the advanced collection architecture with next-generation processing, exploitation and dissemination capabilities to provide the critical information to the decision maker in the constantly changing operational situation. The time to accomplish this, however, is too long, for a scenario of realistic size, to allow recalculation of the results based on short-term contingencies.

A recent SBIR effort, however, ISR Strategy Optimizer, demonstrated the feasibility of using mathematical programming technology to optimize collection strategy selection for scenarios requiring multi-platform coordination and synchronization by developing algorithms that were able to quickly perform (albeit abstractly or coarsely) multiple asset path planning and asset-target assignment and scheduling while also selecting asset types, numbers, and bed-down locations in a global manner. Since ATOs are so interdependent, the ability to quickly recalculate entire theater ISR platform assignments based on unanticipated contingencies allows for the possibility of much more optimal use of ISR platform assets.

And a major part of the just completed DARPA Dynamic Tactical Targeting (DTT) program as well as the new Dynamic Tactical Targeting: Tactical Exercises and System Testing (DTT:TEST) program that is just beginning is a portion of the architecture devoted to Proactive Sensor Tasking, which will provide DTT with a Control component to continuously update plans for future sensor operations, including both the routes that platforms follow, and the collection tasks that sensors perform.

It is anticipated that examination of these efforts as well as other efforts and studies will help to identify new forms of application for ISR platform optimal route determination.

## **- RF Tag Utilization**

RF Tag technology has been under development for many years. Great advances in RF Tag technology were made through the recent DARPA Digital RF Tag (DRaFT) program. Areas where RF Tags have been considered for use include Blue Force communications and tracking. Particular consideration for the potential use of RF Tags has been to help reduce fratricide. The Army's current RF Tags Advanced Concept Technology Demonstration (ACTD) is attempting to demonstrate the utility of the DRaFT device as well as three other RF Tags for these missions. DRaFT was developed with the intent that it possesses great flexibility, giving it the ability to be used for many potential missions. Possible synergistic devices and areas include use with multiple ISR platforms working in concert with RF Tags, their use in concert with UGS as well as with other associated techniques. Investigation of this area is anticipated to lead to the development of useful concepts for improved Blue Force communications, tracking, and other missions.

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